The Effect of Health Expenditure on Inequality: A comparison of methods in Ghana

Jeremy Barofsky[1]
Commitment to Equity Institute and ideas42
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Abstract

This paper measures the effect of health spending on economic inequality in Ghana. I compare three approaches to measuring health spending incidence: the average cost, willingness-to-pay, and aggregate returns methods. The first uses national health accounts to value the average cost of each unit of care. Willingness to pay uses revealed preference care choices and the opportunity cost of accessing care to estimate demand elasticities. The third method, aggregate returns, estimates incidence of health system spending based on its conceptual components such as public subsidies for health care, financial risk protection and improvements in health status. I find that the average cost and willingness-to-pay methods measure similar aspects of health system spending and so produce similar and small effects on income inequality. In contrast, because the aggregate-returns method also incorporates the value of averted mortality and risk protection, it shows that health spending sharply reduces income inequality. This affect is driven by deaths averted both through malaria treatment and prevention.

1. Introduction

Health spending in developing nations has expanded rapidly since 2000. Health expenditure now constitutes 37% and 23% of total government expenditure in low and low-middle income nations, respectively (World Bank, 2015). In addition, multiple developing nations have expanded health insurance coverage, while the goal of universal health coverage even for the poorest countries has received increasing support among multilateral institutions and researchers (World Health Organization, 2010; Jamison et al., 2013). Collectively, these efforts have generated large benefits, with low-income nations gaining over 10 years in life expectancy since 2000. Although transformative, less is known about how government health

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spending translates into changes in economic inequality and especially how these health investments compare against other forms of government spending.

One of the most comprehensive efforts to estimate the impact of taxes and transfers on economic inequality is the work of the Commitment to Equity (CEQ) Institute (Lustig and Higgins 2017). Given that governments can provide support to citizens either through direct spending or in-kind services, these two types of transfers must be aggregated using a money metric for comparison. Currently, CEQ calculates the fiscal incidence of government-provided health services using the officially reported average cost of medical care.

However, the average cost of care does not necessarily reflect a health system's overall welfare impact. First, health-system capture of government spending can constitute a substantial proportion of total spending, meaning much of government health transfers are spent on wages and benefits instead of medical care. This could translate into improved quality of care, but should be captured when the system's health benefits are estimated. Second, because of asymmetric information and moral hazard, some medical care may have minimal health effects or induce demand for unnecessary care. Absenteeism and lack of accreditation is commonplace among providers (Das and Hammer 2005) and quality is low. For example, when presented with hypothetical patients by researchers, 27% of Tanzanian doctors were able to correctly diagnose malaria with anemia and 29% could correctly diagnose diarrhea with dehydration (World Bank 2012). At worst, badly designed health systems may increase the likelihood of catastrophic health spending (Wagstaff and Lindelow, 2008) even if governments are subsidizing care. Third, effective health systems provide benefits to citizens beyond the cost of private care. These include some of the most cost-effective interventions available (eg: oral rehydration therapy, vaccination, deworming medication, clean water, and sanitation) and can generate large health benefits. Indeed, some of the largest potential gains that government produces do not come from the provision of medical care at all, but a disease-free environment through health-related public goods. Moreover, in the benefit-cost analyses performed in the health literature in low- and middle-income nations, little information is provided on the distributional consequences of policy choices (Robinson et al. 2017).

Instead of using the average cost approach – where one dollar of spending is equivalent to one dollar of benefit – this paper describes and applies two additional methods for estimating the in-kind benefit of health spending which relax that assumption: the willingness-to-pay and aggregate returns methods. Using nationally representative data from Ghana, these methods are also applied to measure how health spending affects income inequality. Ghana is chosen as the application to implement these methods because the nation has recently expanded health coverage to the poor, collects high-quality surveys, and has sufficient other data (both experimental and non-experimental) such that a literature exists to support estimates on the efficacy of health system spending. To be directly comparable to the most recent CEQ economic inequality analysis in Ghana (Younger et al. 2015),

the Ghana Living Standards Survey (GLSS) 2012/13 is used, an income and expenditure survey with an extensive health utilization section.

In the willingness-to-pay approach (WTP), the decision to seek care is estimated using revealed preference care choices as the expected benefits of care utilization are compared against the costs. The decision-making model behind this method is that an individual's WTP incorporates both the utility benefits from expected health gains and any pecuniary value that may result from care consumption (eg: financial risk protection and greater labor market productivity). A multinomial logistic regression model is used to capture the individual decision to seek either outpatient or inpatient care. The cost of care is estimated from user fees plus the opportunity cost of time to travel and receive care. Model coefficients are then used to predict demand across various price changes and arc elasticities of demand for each type of care are found. These elasticities are translated into a willingness to pay for one unit of care using an individual's compensating variation. The compensating variations, which measure the value of each unit of care, are then applied to those receiving care and the distributional impact is estimated.

The value and cost of care are associated and, consequently, revealed preference is a more accurate measure of health care's value than assuming value is equal to cost. However, WTP is also limited because it relies on the assumption that individuals are able to accurately estimate the expected health benefit of obtaining care. Psychological biases such as underweighting low probability events, tunneling to the present moment or ostriching, and information asymmetry between patient and provider mean that individual decisions often differ systematically from utility optimization. Moreover, individuals may not effectively act on their intentions (Laibson 1997). Given these biases, there is often a discrepancy between an individual's perception the expected health impact of care. In low-income environments, liquidity constraints and a lack of education and information to estimate returns to health, exacerbate these common psychological biases (Dupas and Miguel 2016). For example, when it comes to preventive health products, demand is highly sensitive to price with a nonlinear demand increase at zero price (Cohen and Dupas 2010). Kremer et al. (2011) find that the WTP for clean water is low in western Kenya and implies the value of statistical life multiple orders of magnitude lower than common estimates from the developed world. Noting this finding, Greenstone and Jack (2015) observe that, because individuals in high disease burden areas do not exhibit high willingness-to-pay to avoid that burden, there is "hardly a more important topic for future study than developing revealed preference measures….that capture the aesthetic, health, and/or income gains from environmental quality." Given that the WTP method is more accurate than the average cost assumption in which spending is equal to value, and its informational requirements are not significantly different than the current CEQ average cost, the method represents a potential option for CEQ.

Nevertheless, given the limitations of revealed preference, I also propose the aggregate returns approach to estimating the benefits of in-kind health spending.

This method involves identifying the incidence of each component of health spending. Conceptually, health spending can generate the following impacts: 1) changes in health status, 2) financial risk protection, 3) subsidies for health care, 4) improved health from health-related public goods, and 5) labor productivity. Each of these could be estimated, although measurement challenges exist, and compared against other forms of income and government transfers. In the following, estimates are developed on how Ghana's health system averts mortality from HIV and malaria, how Ghana's National Health Insurance Scheme (NHIS) provides protection against health shocks across the income distribution. These values are combined with the value of Ghana's subsidies to curative care. Estimates of mortality averted from health interventions such as anti-retroviral therapy for HIV treatment and antimalarial medication are monetized using the value of statistical life literature (Viscusi and Aldy 2003; Ashenfelter and Greenstone 2004).

In general, relatively little is known about how health system interventions affect health inequality. Recently, a few papers have attempted to measure how a given health intervention affects inequality. Using longitudinal data, Costa-i-Font et al. (2017) measure how expanding health coverage in Mexico affects health status inequalities. They find that the distribution of health worsens in Mexico as coverage expands and there is no improvement in health status mobility and conclude that expanded access to insurance did not improve health equality. In addition, Wang and Yu (2016) find health inequality in China worsened substantially over time, but that health coverage was likely not the primary driver of these changes.

For the willingness-to-pay approach, I find that medical care costs are driven by travel time and therefore low compared relative to income. The implied level of income inequality is found to be similar for the average cost and WTP method. Specifically, each indicates that Ghana's final income Gini coefficient is approximately 0.40 and the 90/10 income ratio is about 6. Although the valuation of care differs somewhat between average cost and WTP, these differences are not significant compared to overall income. In addition, the types of care that are being valued (inpatient and outpatient care using the distribution of utilization) is that same. In contrast, the aggregate returns approach incorporates both subsidies to medical care, while also calculating the incidence of financial risk protection from insurance coverage and from mortality averted. The resulting measure of income inequality is found to be lower for aggregate returns compared to the other two methods. Financial risk protection is welfare enhancing, but because high-income households incur the largest health expenditure, the reduction in risk from insurance coverage is clustered in the top income quartile. This implies that the effect of NHIS coverage on risk is regressive. Nevertheless, the welfare value from mortality averted is highly progressive and the magnitude is an order of magnitude greater than care subsidies and risk protection. These results come both from directly progressive policies such as the distribution of preventive malaria interventions as well as antimalarial treatment which is approximately uniform, but produces larger monetary benefits for deaths averted at younger ages. Because lower income families have more children, these gains are also progressive.

Combining estimates to obtain health-inclusive income, the aggregate returns approach yields a Gini of 0.19 and the 90/10 income ratio 2.27. By expanding the types of health system interventions valued beyond curative care, the aggregate returns method permits governments to better elucidate how health-spending choices impact welfare across the income distribution.

This paper proceeds as follows: section 2 describes the average cost method briefly, providing additional references for further background, section 3 details the willingness to pay method, how it is applied to Ghana, and what it implies about how health spending impacts inequality. Section 4 describes the aggregate returns method, estimates the value of mortality averted from malaria and HIV interventions in Ghana, values financial risk protection from insurance coverage, and calculates effects on inequality. In addition, how to value health-related public goods provision is described. Section 5 compares the methods and how each affects economic inequality, while 6 concludes.

2. Average Cost Method

Previous analyses carried out by CEQ value health spending by using an average cost with usage approach, which is also commonly referred to as basic incidence analysis (BIA) applied to health spending (O'Donnell et al 2008). That is, in-kind health transfers are valued based on the use of public services and their average cost as reported in government national accounts. This process requires three principal steps: First, utilization of public health services is compared to a measure of living standards (usually income or consumption). Second, each individual's (or household's) health utilization is weighted by the unit value of the public subsidy for that service. At a minimum, CEQ analyses use health data that separates utilization into inpatient and outpatient care. Third, the distribution of health subsidies is evaluated against a target distribution. Only publicly subsidized health services are included.[2] This includes funding from development assistance for health (DAH), user fees, and social insurance if these revenues are determined by the state. Total annualized health system benefits are calculated as the number of services received multiplied by the cost of that service, summed over all health service types and normalized by recall period to be yearly.

To calculate average cost, aggregate data on total government spending by health service type is required. Younger et al. (2015) carries out the CEQ benefit-incidence analysis for Ghana using the same data used here, which includes estimating the value of both inpatient and outpatient but not other component of health system spending. Outpatient care average cost is used from Ghana's Ministry of Health (2014) cost of provision data. For inpatient care, the Ministry of Health had data on cost of provision from Korle Bu hospital, the main teaching hospital in Accra and

[2] In Ghana, private health insurance covers less than 1% of the population. However, in other nations, if households receive care and are covered by private insurance, they are assumed to have received private care and therefore did not receive an in-kind public transfer (Lustig and Higgins 2013).

includes both outpatient and inpatient care.[3] Calculating average cost this way is known to overestimate the redistributive effect of health transfers because by construction their value will equal their cost from national accounts data while totals from other taxes and transfers in CEQ come from self-reported consumption and expenditure surveys and therefore systematically lower. To correct the overestimate, the value of health transfers are scaled such that value of health transfers to disposable income is equal to ratio of health to disposable income from the survey used. Under the average-cost method, when government subsidizes insurance coverage instead of care directly, the value and incidence is estimated as the average public cost of that insurance program applied to those with that coverage. That is, the value is applied not for those that receive care but across all those that are covered by the insurance program. Below, this insurance value is contrasted to the aggregate returns method, which insurance value is defined as the causal impact of financial risk protection provided by a given insurance program.[4]

3. Willingness to Pay Method

3.1 Overall Strategy

In the following section, the willingness to pay method is used to estimate the revealed preference value of inpatient and outpatient care. To estimate an individual's willingness to pay for health care choices, a demand function must be specified and price elasticities estimated. An important issue when using revealed preference to measure individual valuation of medical care is how price-sensitivity varies by income levels. Given the increasing evidence that the poor are more price sensitive than the rich, particularly with a nonlinear shift in demand at a zero price, observed shifts in utilization may underestimate the value of health care access.

In the following, I derive a discrete choice specification of medical care demand from a utility-maximizing theoretical model using a previously developed literature on how user fees can be used to finance medical care in the developing world (Gerlter, Locay, and Sanderson 1987, Gertler and van der Gaag 1990). Then, the estimated demand equation for medical care is used to compute compensating variations (willingness to pay), which later will be used to estimate how government provided health care affects economic inequality. The model relies on the observation that when there is no price variation, quantity is rationed based on nonmonetary costs, in this case, the opportunity cost of time to access care through travel (Becker, 1965).

3.2 Modeling the Demand for Health Care

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[3] They obtain an estimate of the average cost of inpatient spending in Korle Bu hospital by itself by subtracting from the total expenditure at Korle Bu, the number of outpatient visits by their national estimate of its cost and divide by reported inpatient procedures performed at the hospital.

[4] See Younger et al. (2015) for further details in Ghana and Lustig and Higgins (2017) for a further description of the average-cost method to value the incidence of health spending.

After an illness, individuals must decide whether to seek medical care and if they decide to buy care, the type of provider to see. Individuals are modeled to experience utility from either consumption in the current period or their health status. Formally, utility from choosing care from provider j is modeled as the following:

(1) $U_j = U(H_J, C_j)$

where H_j is expected health status after receiving care from provider j, C_j is consumption of non-health goods after paying provider j. The expected improvement in health after going to provider j is the perceived quality of care or the marginal product of care from provider j. This can be modeled as:

(2) $H_j = Q_J + H_0$

where H0 is expected health status after self-treatment and Q_j is the additional improvement in health status from obtaining care from provider j. This can be seen as the perceived quality of care from provider j. Q_j varies by provider and also by individual characteristics such as illness severity, age, and education level. The health production function normalizes the quality of care against the self-care option where $Q_j = 0$ and $H_j = H_0$.

Consumption expenditure is defined as net consumption after the price of care from provider j has been incurred. The total price of medical care is equal to the price paid for care, the nonmonetary opportunity cost of time to travel to provider j and the any direct transport cost as well. Given these definitions, the budget constraint is

(3) $Y_j = C_j + P_j^*$

Plugging in (3) into (1) yields:

$U_j = U(H_j, Y - P_j^*)$

Given that the cost of health care includes both the monetary cost of care, the monetary cost of travel, and the opportunity cost of time for travel, it is assumed that the lost time from seeking care comes out of the work or home production time instead of leisure.

Each individual maximizes their utility across the choice of alternative providers and if random terms are included in the model, choices are defined by the probability an individual chooses a given provider. In a discrete choice model, these probabilities are demand functions, conditional on income and provider price,

where the probability that an alternative is chosen is the same as the probability that the given alternative maximizes an individual's utility.

3.3 Estimating Demand for Health Care

I follow Gertler and van der Gaag (1990) and use a conditional utility function of the semiquadratic form because it permits variation in the rate of marginal substitution between health and consumption. This variation in the MRS between health and consumption is required for health to be normal good and this functional form allows the data to determine the relationship between income and health care choice. Specifically, the utility function assumed, linear in health and quadratic in consumption, is the following:

(4) $$U_j = \alpha_0 H_j + \alpha_1 C_j + \alpha_2 C_j^2 + \epsilon_j$$

Since consumption for a given provider choice (C_j) is defined net of the price of care provider j, formally Cj is defined as:

(5) $$C_j = Y - (P_j + wT_j + D_j)$$

where Y is consumption and P_j is price for provider j, wTj is the opportunity cost of time for travel, and Dj is the direct cost of travel. Substituting (5) into (4) such that the budget constraint is incorporated explicitly and creating the conditional utility function and subtracting Uj – U0 illustrates that if α_2 doesn't differ from zero, then income does not affect care choices. And prices do not influence care choices if both α_1 and α_2 are equal to zero (Gertler and van der Gaag 1990).

Quality of care or the marginal product of health care by alternative, along with price, determines choice. Plugging equation (2) into (4), produces the conditional utility function as the following form:

(6) $$U_j = \alpha_0 H_0 + \alpha_0 Q_j + \alpha_1 C_J + \alpha_2 C_j^2 + \epsilon_j$$

However, quality (Q_j) is unobserved and therefore must be estimated. Q_j conceptualized as determined by both provider characteristics and a household production function that translates medical care into action that jointly determine the effectiveness of care. In addition, marginal utility of quality is assumed to vary by sociodemographic characteristics.

Following, Gertler and van der Gaag (1990) quality is specified as a set of socio-demographic characteristics and to make the specification of quality general, coefficients vary by alternative:

(7) $$\alpha_0 Q_j = \beta_{0j} + \beta_{1j} X + \eta_j$$

where X is a vector of determinants of quality and utility from quality. By plugging (7) and the budget constraint, equation (5), into (6) the following is obtained:

(8) $U_j = V_j + \eta_j + \epsilon_j$

where

(9) $V_j = \beta_{0j} + \beta_{1j}X + \alpha_1[\,Y - P_j - wT_j - D_j] + \alpha_2[Y - P_j - wT_j - D_j]^2$

where (9) is the indirect conditional utility function used for estimation. The β intercept and coefficients, the determinants of quality, are indexed by j and therefore vary by care alternative, while the α coefficients on consumption are constant across care choices. The random error in the quality equation η_j is assumed to equal zero in the case of self-care, but these disturbances can be correlated across care choices. We are able to test empirically whether there is correlation between medical care choices.

To estimate empirically what medical care choice maximizes an individual's utility, a multinomial logit (MNL) model is used. The MNL estimates the probability of discrete choices using variation in characteristics of the health production function (determinants of quality) and the total price of health care including the opportunity cost of time (to be discussed below). The MNL model imposes the independence of irrelevant alternative (IIA) assumption, which in this context, implies that error terms are uncorrelated between inpatient and outpatient care types. Given the limited choice set, this is a reasonable assumption although further work could use a nested multinomial logit model to relax and test IIA empirically.

The medical care choices modeled vary by the nation's health system. In Ghana, individuals primarily decide between inpatient and outpatient care. If insured, the vast majority of individuals are covered by the NHIS those paying out of pocket, can access both public and private care.[5] Therefore, in Ghana, the choice to seek care is modeled as a choice on whether to seek any care at all, and then, conditional on seeking care, the choice between whether an individual chooses outpatient or inpatient care. That is, there are two "nests" of choices: self-care versus some form of care. Self-care, however, is a degenerate nest without any choices within it, so no parameter on the correlation of errors within those choices, τ_m, is estimated.

The estimated demand functions (the probability of choosing a given care alternative) are used to calculate an individual's willingness to pay (WTP) for medical care. WTP is calculated by calculating each individual's compensating variation, which represents the amount of income that would compensate an

[5] A facility must be accredited for care to be covered by NHIS. An expanding number of private facilities in Ghana were accredited in 2013, though not all, and given that we cannot differentiate between them, we assume that all private facilities accepted NHIS coverage.

individual to receive the same utility the individual received before a change in price or quantity.

3.4 Compensating Variation and Willingness to Pay

The welfare effect of a price change involves both an income effect (reduction in net consumption and a substitution effect (change in the probability of making a health care choice). To calculate the CV, the unconditional indirect utility and expenditure functions must be found. Following Small and Rosen (1981) and Gertler and van der Gaag (1990), we define the CV in the following way:

$$(10)\ \ CV = \left(\frac{1}{\lambda}\right)\{\ln(e^{V_0} + [\sum_{j=1}^{J} e^{\left(\frac{V_j}{\sigma}\right)}]^{\sigma}) - \ \ln(e^{V_0'} + [\sum_{j=1}^{J} e^{\left(\frac{V_j'}{\sigma}\right)}]^{\sigma})\}$$

where V_0 and V_0' are evaluated at prices that imply for each individual a decline in quantity of one unit of care for outpatient and inpatient care respectively. That is, I calculate the price elasticity of demand for care. Then I translate this into a change in price that implies a reduction in care equal to one unit. Then, the CV represents the value each individual attributes to one unit of inpatient and outpatient care.

The parameter λ represents the marginal utility of income. The parameter λ is not independent of price, since the marginal utility of income is still a function of both income and price with the semi-quadratic utility function. The value of λ is approximately the same over different prices of medical care as long as price is small relative to income. That is, we can assume that that the marginal utility of income does not vary by individual across price changes as long as those price changes are small relative to income. Nevertheless, given the wide variation in incomes across individuals, the marginal utility of income likely varies significantly across individuals as well.

3.5 Data

The data used is the GLSS 2012/13, chosen for comparison to CEQ's recent Ghana analysis by Younger et al. (2015). In addition to its health utilization module, the GLSS, includes a rural community survey, which asks about travel times and distance at the community level for various types of health facilities.

In Ghana, of the individuals who report being sick or injured in the last two weeks, 48% choose self-care, 46% choose outpatient care, and 4.4% choose inpatient care. Those seeking care from traditional providers or in a provider's home are excluded from the analysis (1.7%) and those seeking care at pharmacies or chemical stores are coded to self-care (14%). Conditional on reported illness or injury in the last two weeks, the discrete choices modeled are whether the individual receives any care at all (self-care), and if they seek care, whether the receive either inpatient or outpatient care.

Income is calculated as the average monthly value of total household consumption. This assumes that the household's per period budget constraint is monthly income (total consumption) and that they are constrained from borrowing. Given that in fact the vast majority of care costs are determined by the opportunity cost of travel and waiting time, this is deemed a reasonable assumption. Net consumption then, as described above, is defined as monthly total household consumption minus each provider price of medical care for those that received care (described in more detail below).

The socio-demographic characteristics included in the model that affect the household production of health include age (split into indicator variables for infants under two years old, ages 3 to 5, ages 6 to 18, ages 41 to 60, and ages over 60), education (either own or mother's for children or if missing), an indicator variable for mother's education used, number of adults in the household, number of children in the household, age, and severity of illness (number of days reported sick in the last two weeks).

3.6 Calculating the cost of medical care

To calculate a demand function using the MNL model that is consistent with utility maximization in equations (8) and (9), the cost of medical care for each care choice must be estimated. The cost of each medical care choice is determined by the out-of-pocket price an individual would pay plus the opportunity cost of travel and wait time. In Ghana, the GLSS 2012-13 includes a community survey for rural areas that ask about travel time to the nearest health care facility. For rural households, the opportunity cost of time is calculated by using the community survey's measure of agricultural wage by village.[6] Male and female opportunity costs of time are set to agricultural wages rates from the community survey, respectively. For children, their opportunity cost of time is set to female agricultural wages. In addition, the community survey's village-level questions on travel time to the nearest clinic and hospital are used to estimate the time needed to obtain outpatient and inpatient care.

For urban areas, where the GLSS community survey is not available to estimate either distance to health facilities or the opportunity cost of time, self-reports are used instead. To estimate the opportunity cost of time in urban areas, annual household income is used and divided to obtain an hourly wage per household. For urban households that report zero total wages earned (13%), I replace their opportunity cost of time with the minimum reported hourly wage in their district. Since there is no community survey, travel times to outpatient and inpatient care in urban areas are calculated from the median self-reported travel time by cluster and, if missing, by region.

[6] The wage is the mean of all types of agricultural work (clearing, planting, harvesting, and other). For households in villages without agricultural wage information (13% for female agricultural wages and 7.5% for male agricultural wages), the mean regional agricultural wage is used instead.

To estimate the price of inpatient and outpatient care, a combination of health system structure and self-reports are used. For those with membership in the NHIS, no coinsurance, copayment, or deductible is required at the point of service (Nguyen et al. 2011). Therefore, out-of-pocket prices for NHIS members (66% in urban and 61% of the self-reported sick or ill) are set to zero. This is consistent with what is observed empirically as approximately three-quarters of individuals accessing inpatient and outpatient report paying no out-of-pocket fees at the point of service. The GLSS asks questions on outpatient price paid for care overall and the price by stage of care (registration, consultation, diagnosis, drugs and treatment). Because the price paid for the stages of care does not always sum to the reported total, the maximum of these two measures is used for outpatient care out-of-pocket price. Once defined thusly, prices for outpatient and inpatient care are estimated using the median self-reported costs for those without NHIS coverage per cluster for outpatient and per region for inpatient care. Even among individuals without NHIS coverage that were hospitalized in the last two weeks, the median reported inpatient fees are zero. Given this, we set inpatient costs to zero. OOP outpatient fees paid for those without NHIS coverage are set at the district median.

3.7 Empirical Results

Table 1 shows the summary statistics by urban and rural households and overall for variables using the sample included in the MNL model (those individuals reporting using for data used in the MNL model, which is 14.4% of all individuals). The table shows that almost half and slightly more than half of those reporting being sick or ill in the last two weeks practice self-care instead of using any formal medical care. We also observe that 46% and 49% of sick individuals, respectively, received outpatient care and about 4% of sick individuals received inpatient care in the last two weeks.

Table 2 displays the multinomial logistic regression results for both inpatient and outpatient care for rural and urban households separately. It is observed that the net consumption is positively associated at a decreasing rate with outpatient and inpatient utilization in rural and urban households. This concavity is consistent with diminishing marginal utility of consumption for care. It also observed the number of reported days sick is highly significant in predicting utilization and being male is associated with a reduction in use for outpatient care in both rural and urban areas.

Table 3 shows the estimated arc elasticity of demand for outpatient and inpatient for urban and rural households as total cost of care is shifted from 0 to 20 and 20 to 40 $GHC. These intervals are chosen because they are in-sample prices given that the mean of total cost for outpatient and inpatient is 22 and 24, respectively. The IQR for cost of each care type is about 7 to 30 $GHC. The arc elasticities between each price point are obtained by setting all variables in the model to their mean based on urban status and national income quartile, then old or new price is subtracted from monthly consumption and demand is predicted. Table 3 indicates that elasticity is negative and decreasing with income quartile, as expected. For

outpatient care, demand is more responsive to price changes in urban compared to urban areas. For inpatient care, demand also is more elastic for rural consumers than urban. These values are then translated into CV as described above. To be discussed later, table 10 summarizes the WTP valuations (along with average cost and aggregate returns), while table 11 shows the implication of each method for income inequality.

4. Aggregate Returns

4.1 Overall Strategy

Conceptually, the benefits of government health spending can be separated into five categories: 1) changes in health status, 2) financial risk protection, 3) subsidies for health care, 4) health-related public goods, and 5) labor productivity. In the following, I describe how each of these components could be estimated and calculate values for the first three using the same data set from Ghana used for the average cost and willingness-to-pay analysis to obtain a health-spending inclusive measure of final income.

The primary justification for in-kind health spending is to improve population health. Data from nationally representative surveys is used to estimate access by income group to health interventions intended to reduce HIV, malaria, immunization, and non-communicable disease (NCD)-related mortality. Projection methods are then employed to estimate how access to these interventions affects mortality across the age distribution. That is, the aggregate returns method allows a comparison of the projected health benefits and incidence of both preventive and curative health interventions. In contrast, the average cost and WTP approach focus exclusively on the incidence benefit of curative health care interventions. Changes in mortality by income group are valued using the value of life years (VLYs) approach Jamison et al. (2013). Mortality is monetized based on national income and the age at which mortality is averted such that mortality averted at younger ages is valued more highly than mortality averted at older ages.

Subsidized health care and health insurance is also valuable because it reduces the risk of expensive health shocks for risk-averse families. This benefit is estimated by calculating the distribution of health shock spending for those with and without Ghana's NHIS insurance by income quartile. To obtain an insurance value, a stylized utility model is employed to estimate the change in the risk premium implied for a given reduction in risk, assuming various estimates of risk aversion and consumption floors for health shocks. Even when health care does not provide any health status benefit or financial risk protection, public subsidy of care provides the user a value equal to the cost of the health spending.

In addition, I describe how mortality averted from the provision of two types of health related public goods can be estimated: access to sanitation and water infrastructure. Research to value public goods provision going back to at least Aaron

and McGuire (1970) uses consumer preferences for public goods as the determinant of value. This estimate is subject to similar criticisms as described above related to willingness-to-pay estimates using revealed preference. This approach instead, is consistent with a causal impact effect to estimate mortality averted from the provision of health-related public goods. Access is calculated from the GLSS and the value of averted mortality is estimated using methods from Jamison et al. (2013). Benefit-incidence analysis (BIA) often falls short in valuing government spending on in-kind transfers, particularly public goods, because of difficulties in measuring impact and assigning it to individuals (O'Dea and Preston 20112) and CEQ has not previously included the valuation and incidence of health-related public goods.[7]

The final conceptual benefit of health spending (labor productivity gains) is important given the increasing evidence that childhood malaria produces reduces long-term schooling and earnings potential (Bleakley 2010, Cutler et al. 2010, Lucas 2010, and Barofsky et al. 2015) and HIV treatment leads to close to full employment recovery for HIV-positive adults (Bor et al. 2013) in addition to having spillover effects on those who are HIV negative by encouraging human capital formation (Baranov and Kohler 2017) and increasing employment (Wagner, Barofsky, Sood 2014). Although noted conceptually, I do not estimate the impact of health investments on labor productivity given the time horizon.[8]

4.2 Estimating Averted Mortality

Health is both an intrinsic and instrumental goal. Better health is valuable in itself, while also permitting individuals to achieve other goals they value such as an education and greater labor productivity. Since the primary goal of health care is improving health, the aggregate returns method estimates the impact and incidence of health improvements from health system interventions. Although the most important measure of health system efficacy, estimating health gains presents empirical challenges, especially in developing nations. Methods known to produce unbiased estimates of program impact such as experimental or quasi-experimental methods are particularly ill-suited to this task because health gains are often long-term, cumulative, and relatively rare events (meaning sample sizes may be underpowered to detect an effect). Moreover, as developing nations undergo the epidemiological transition, a larger percentage of health gains are mediated by risk factors that affect the incidence of non-communicable diseases. However, because detailed information on the dynamics of disease spread exists along with clinical

[7] There are, of course, other important health-related public goods that provide substantial health benefits, most notably vaccination, air pollution restrictions, and malaria control within endemic nations. However, we focus here on the mortality effect of water and sanitation infrastructure because of data availability. Future analyses however would be expected to expand measurement of the distributional provision of health-related public goods because of their significant effect on human capital formation.

[8] In Barofsky (2018, Handbook chapter) a more robust description of the potential scale of these economic gains and how to estimate them is provided.

trial evidence on the efficacy of a wide range of medical interventions, the an estimate of how these interventions affect mortality rates can be made. Given data on how these interventions vary by income group, the incidence of these changes in mortality across the income distribution can also be calculated.

Table 4 shows that top 10 causes of premature death in Ghana. Premature death is defined as the number of years of life lost (YLLs) attributable to a given disease. Because remaining life expectancy for those aged 15 to 19 in Ghana in 2013 was 52.5 years (Global Health Observatory 2018), a death for someone aged 15-19 generates 52.5 YLLs. That is YLLs weigh deaths at younger ages more than older ages, based on a nation's remaining life expectancy.

Table 5 provides a schematic of the types of care that a health system provides, separated into personal and public health interventions as well as interventions that cure disease (either over the short- or long-term) versus those that prevent disease. This distinction is important because the other CEQ approaches – average cost and willingness to pay – focus exclusively on personal and curative care, while preventive care and publicly provided interventions can have large health benefits. Because these interventions can also be highly cost-effective, progressive provision is more financially and politically feasible than personal curative care. That is, without estimating their effect, analysis may miss important aspects of a health system's distributional effect. In addition, curative care can be further separated into acute and chronic care. Acute curative care cures that disease for the future. In contrast, chronic care requires continuous follow up treatment. For example, ART is chronic curative care. Therefore, one year of ART averts mortality with the assumption the individual receives ART also in all subsequent years. That is, for chronic and acute curative care that averts a death this year, the chronic care implies a long-term future monetary obligation, where acute curative care does not.

Mortality change from a given health intervention is projected using the Spectrum software package, developed by Avenir Health (Avenir 2014). Spectrum is a system of policy models used to examine the impact of changes to health interventions for use by researchers and policymakers. Each projection starts with results from the demographic model that estimates changes in population using data on fertility, mortality, and migration rates. The demographic model comes prepopulated with country-specific data and estimates from the United Nations Population Division. Built on these demographic projections, disease specific models were created to model changes in mortality from HIV, malaria, child and maternal health, and non-communicable diseases. Each disease model combines robust science on disease transmission and intervention efficacy using scientific literature review with country specific data from sources such as UNAIDS and nationally representative surveys such as the Demographic and Health Surveys. Data sources are updated annually or as frequently nationally representative surveys are conducted in a given country, while research literature is reviewed frequently to ensure efficacy parameters are up-to-date.

Across causes of death, to coincide with estimates useful to CEQ analysis, changes in mortality are estimated by comparing current levels of health intervention coverage against counterfactual levels of coverage that would prevail without government health spending. Best estimates on the counterfactual level of health interventions without public involvement depends on the development of a nation's private health care market. In addition the counterfactual level of health spending depends on the type of health intervention. Especially for higher income groups, public provision of acute care could be substantial. In contrast, most preventive and public goods health intervention would not be provided without government action. Given Ghana's lower-middle income status and minimal level of private health insurance, the counterfactual assumption for all health interventions without government intervention is no provision of that service. The change in mortality using the Spectrum software therefore is estimated by comparing, for example, malaria mortality with current levels of antimalarial medication against a situation where no one is treated with antimalarial medication. This will tend to underestimate the inequality benefits of health interventions because access to these interventions among low income groups would indeed be close to zero without government support, while access would increase monotonically as income rises. In the following, these projections are made comparing mortality under current levels of health coverage against the counterfactual of no coverage. Total mortality averted is then distributed across income groups based on data by access to the health intervention being analyzed by wealth quintile. The results causes of death are presented below for HIV and malaria. After showing how changes in age-specific mortality rates are calculated, section 4.3 describes how these mortality changes are translated into monetary terms to be compared against other government transfer options.

4.2.1 Malaria

Malaria is a vector-borne parasitic disease spread by mosquitoes that, in 2016, produced 216 million cases and 445,000 deaths worldwide (World Malaria Report 2017). Over 90% of these deaths occurred in sub-Saharan Africa and almost all of these deaths were in children under 5 years of age. In Ghana, malaria is the number of cause of premature death and directly caused an estimated 13,940 [12,240, 15,650] deaths in 2013 (World Malaria Report 2017).

Public health systems have four primary anti-malarial measures available: 1) insecticide treated mosquito nets (ITNs) – nets treated with insecticide, which both kills mosquitoes as well as protect individuals at night from mosquito bites, 2) indoor residual spraying (IRS) in which households are sprayed with chemicals to kills mosquitoes, 3) use of antimalarial medication when malaria is either suspected or confirmed with test results, and 4) use of prophylactic antimalarial medication for pregnant women vulnerable to malaria infection. As much of sub-Saharan Africa, Ghana has experienced a rapid decrease in malaria-related mortality. From 2010 to 2016, malaria-attributable deaths declined by 20% (World Malaria Report 2017).

When it comes to provision of malaria-related interventions, most households sprayed with IRS receive it from government (53%) or non-governmental programs (18%), and the other largest category is spraying by private companies (15%, GDHS 2014). In addition, most ITNs are provided free through Ghana Health Service and MoH through mass distribution campaigns and schools, child welfare clinics, antenatal clinics. Also, it is important to note that first line antimalarial treatments are estimated to retain close to 100% efficacy in the sub-Saharan Africa, meaning that deaths averted from treatment can be directly estimated from malaria prevalence and access to treatment by wealth quintile.

To estimate the effect of malaria-related deaths averted by government health spending, this analysis focuses on the provision of three types of interventions: ITNs, IRS, and antimalarial medication. Using the Spectrum software, the change in malaria-related deaths for each intervention is estimated using the counterfactual assumption that the intervention would not be provided without government support. The Spectrum-Malaria module is based on statistical regressions models fit to a large set of simulations using the computationally intensive dynamical malaria transmission model called OpenMalaria (Spectrum-Malaria 2016).[9] Projections comparing current coverage levels to the counterfactual of no coverage for each intervention (ITNs, IRS, and antimalarial medication) are then estimated using Spectrum. The result is an estimate of overall reduction in malaria mortality and changes in age-specific mortality rates for each intervention. This change in age-specific mortality is distributed across income groups using data from the Ghana DHS 2014 on access to each intervention type by wealth quintile. Table 6 shows access how access to the three primary malaria interventions varies over household wealth quintiles. It can be observed that access to ITNs, IRS, and antimalarial medication is highly progressive. But that even with this level of access, malaria prevalence in children age 6 to 59 months is many times higher in the lowest two wealth quintiles than the highest two. This is the result of high malaria risk in rural and low-income areas.

4.2.2 HIV

The human immunodeficiency virus (HIV) is a sexually transmitted disease that causes AIDS. Left untreated, an HIV positive individual can expect to live approximately 12.5 years after infection. Since the development of antiretroviral therapy (ART) that treats HIV, if the treatment regimen is adhered to, an individual with HIV can attain a life expectancy similar to that of HIV negative individuals. In addition to transmission through sexual activity, HIV can be transmitted through between a mother and infant during pregnancy, childbirth, and breastfeeding. In

[9] OpenMalaria was developed by researchers at the Swiss Institute of Tropical Hygiene and Medicine and simulates the dynamics of malaria transmission and epidemiology in mosquito and human populations, and the effects of malaria control. These statistical impact functions (described in Korenromp et al. 2016) are combined with a database of malaria endemicity and epidemiology at the subnational to project future burden.

Ghana, HIV/AIDS is a significant cause of death and the fourth leading cause of premature mortality. Between 2005 and 2013 Ghana experienced a more than 50% decline in AIDS deaths (Granich et al. 2015), however HIV prevalence remained approximately 2% of the population aged 15-49.

The primary driver of reduced AIDS-related mortality was the expansion of access to ART. Similarly to the projections for malaria, an HIV-specific model within Spectrum, the Spectrum-AIDS Impact Model (AIM) is used to project how ART reduces mortality overall. Then, Ghana DHS data on HIV prevalence by wealth quintile is used to estimate how those averted deaths are distributed across the income distribution. The counterfactual projection from Spectrum-AIM implies that Ghana's efforts to treatment HIV averted 11,055 [7,686, 15,306] in 2013. Table 7 shows how HIV mortality is distributed by wealth quintile for men, women, and overall among those aged 15 to 49. It is observed that HIV prevalence peaks among women in the fourth wealth quintile, but among men in the second. Because of this pattern, overall prevalence is uniform across the middle 60% of the wealth distribution. In addition, prevalence levels for women are more than double the level for men.

4.2.3 Cardiovascular Disease and Risk Factors

The Ghana DHS 2014 was the first national survey in the country to measure blood pressure (BP) among consenting adults ages 15 to 49. Survey interviewers used a digital device to take three measures of BP.[10] The survey found that the prevalence of hypertension is a risk factor that is increasing in wealth in Ghana. Table 8 shows the monotonic increase in hypertension prevalence by wealth quintile. This is even more pronounced because of the treatment pattern. The table also shows that the percentage of those with normal BP and taking BP medication is rising in wealth for women, and mostly rising in wealth for men as wealth (with a drop at the highest wealth quintile). In contrast, use of any tobacco by men (although small overall at 5.1%) has a progressive pattern such that over 10% of men 15-49 in the lowest wealth quintile use any form of tobacco compared to 1.2% of men 15-49 in the highest wealth quintile. Tobacco use is close to 0 for all women across wealth levels. Although the distribution of these risk factors is not used to estimate averted mortality from

4.3 Valuing Averted Mortality

Reduced mortality is valued using concepts from the value of statistical life (VSL) literature, which calculate the elasticity of income with respect to mortality risk. VSL studies are scarce for low- and middle-income nations. Most commonly, the VSL is calculated by comparing variation in mortality risk over various occupations against the wage differentials between jobs. In a review, Viscusi (1978) observes that the

[10] Hypertension is defined based on WHO guidelines as systolic blood pressure > 140 mmHg or diastolic > 90 mmHg.

VSL is increasing in income and wealth, consistent with a wide range of papers that find demand for health is highly income elastic (Hall and Jones 2007).

The most comprehensive literature review of compensating differentials studies in the U.S. finds VSL to be between $4 million and $9 million, while a worldwide meta-analysis finds income elasticity point estimates of between 0.5 and 0.6 (Aldy and Viscusi 2002). Aldy and Viscusi (2002) note however that any specific VSL value "should not be considered a universal constant, or some `right number,'" (p. 18). Instead, VSL reflects the wage-risk trade-off preferences of the sample analyzed. VSL represents the elasticity of income with respect to mortality risk, however VSL studies are scarce for low- and middle-income nations.[11]

I approach measurement of mortality gains by following Jamison et al. (2013)'s full income approach to value mortality reduction. Similar to Jamison et al. (2013)'s full income, I also use Hammitt and Robinson (2011)'s estimate that the value of a decrease in mortality risk of 10^-4 (defined as a standardized mortality unit (SMU)) in high-income nations is equal to 1.8% of GDP per capita. This assumes an income elasticity of VSL such that it remains a constant proportion of income across nations. In addition, Jamison et al. (2013) adjust VSL by age based on the years of life lost at a given age of averted death in direct proportion to the number of years of life lost from death at age 35. This means that deaths averted at younger ages are given greater value proportionally to expected years of life at 35. Age 35 is used because this is the mean age from the empirical estimates of VSL in Viscusi and Aldy (2003). I also follow their decision to adjust downward by 50% for mortality changes for those 0-4 year old.

The following, adjusted from Jamison et al. (2013, appendix 3, p.4), provides the annual per capita value of an increase in life expectancy from e_i to e_j years when translated into a shift in SMUs:

$$V(y, e_j, e_i, d) = \sum_{d=1}^{10} [\, 0.018y \int_{a=0}^{5} n(a)\, \Delta SMU(e_j, e_i) \left(\frac{e(a)}{e(35)}\right) da]$$

where y is national per capita income, n(a) is the distribution of the population by age a, and e(a) represents the expected number of years remaining for an individual who has survived to age a. Total value is then obtained by summing over expenditure groups, which here are indexed by income deciles d. When the changes in age-specific mortality rates occur for those ages 0 to 4, the monetary value of 1.8% of GDP per capita is halved. Note also that although the value of statistical life

[11] Most commonly, the VSL is calculated using wage differentials. Meanwhile, it has been observed since Viscusi (1978) that the VSL is increasing in income and wealth, consistent with a wide range of evidence that finds demand for health is highly income elastic (Hall and Jones 2007). However, the lack of data on wage differentials as well as endogeneity of risk selection into given job categories present limitations to VSL estimates in developing countries. In addition to income elasticity, this application must also address variation in the VSL by age.

is assumed to proportional to income across nations, within a nation, VSL is equal. The implicit assumption is that from the social planner perspective, eliminating the death of one citizen is equally as valuable irrespective of that citizen's income.

4.3.1 Results from Valuing Mortality Averted

Figure 3 depicts the value ($GHC) of mortality averted by income quintile. The relationship is driven by the large mortality burden of malaria in Ghana. Of the three interventions that reduce malaria – antimalarial medication produces the largest and most immediate gains in mortality. As was shown, access to antimalarial medication is approximately uniform across the income distribution. However, if another assumption on the counterfactual distribution of access was used (to incorporate the greater access to private sources of medication for higher incomes households), the progressive impact of malaria treatment would be greater. Nevertheless, although figure 3 shows that the value of mortality averted is similar across incomes, because the value of averted mortality is also higher for younger ages, Ghana's age distribution (more children in poorer households) mean that the provision of antimalarial medication is progressive. In addition, because the age pattern is the same for deaths averted from IRS and ITNs and use of these services is also higher among the poor, these interventions are even more progressive than antimalarial medication. Because HIV prevalence is approximately uniform across the income distribution and the mortality benefit accrues at prime ages, the value of HIV treatment, although large does not substantially affect the distribution of health-inclusive income.

4.4 Valuing financial risk protection

Even for actuarially fair insurance, risk-averse households still benefit from insurance coverage through protection against the risk of health shocks. This welfare gain accrues to all covered households even if no health care is used. In Ghana, nearly all those that are covered by any health insurance coverage are covered through the National Health Insurance Scheme (NHIS). The NHIS began as separate district-based and mutual health insurance schemes and was rolled out nationally in 2004 (Duku et al. 2016). To increase access to care among the most vulnerable, statutorily the NHIS provides coverage without premiums to children under 18 years old, elderly aged 70 and above, and pregnant women, and members of Ghana's conditional cash transfer program. In addition, formal sector workers pay into the system through payroll taxes, but are exempt from paying the NHIS premium. Given that over 90 percent of total health insurance coverage in 2012/13 GLSS is provided by the NHIS (Figure A.1), this estimate is close to comprehensive for measuring financial risk protection from insurance coverage in Ghana.

4.4.1 Estimating the effect of insurance on health spending

The value of risk protection from insurance is calculated in two steps: First, the causal effect of health spending by income group is estimated using quantile

regression. Counterfactual health spending for those without NHIS coverage is estimated using coarsened exact matching (Blackwell et al. 2009) to obtain a control group similar in a range of observable characteristics to those with coverage. Specifically, using the GLSS 2012/13 those with NHIS coverage are matched by the following variables: days sick in the last two weeks, days spent in the hospital in the last two weeks, the number of children under 5 and adults over the 70 in the household, and the household's market income. Once treated and matched controls are identified, the quantile treatment effect of coverage is estimated across the health spending distribution and, because health care is a normal good, separately by quartile of household market income. Using these matched regressions, the quantile sample average treatment effect on the treated (SATT) is obtained, which represents the difference in health spending for those with and without NHIS insurance across the health spending distribution. Quantile regression standard errors are clustered at the survey cluster level.

Table 9 shows summary statistics for out-of-pocket (OOP) health spending and market income by household overall and separated by market income quartile. The top panel shows the distribution of OOP health spending is highly skewed such that the median is 0 per household, except for the top income quartile. Mean health spending is 4.7% of household market income overall and ranges from 4% to 6.9% by income quartile. However, the 90th and 95th percentile of health spending represents 9% and 18% of market income overall. It can also be observed that the mean and each centile of health spending increases monotonically with income quartile. For example, the 75th percentile of health spending ranges from GHC65 to 468 by quartile.

Figures 4-7 show the quantile treatment effects and their confidence intervals for household market income quartiles 1 through 4 using coarsened exact matching to create control groups. Since health spending is highly skewed, treatment effects (reductions in health spending from insurance coverage) are small at lower centiles of health spending and rise rapidly above the 90th quantile, indicating that for the highest spending groups, insurance coverage provides increasingly important coverage against catastrophic shocks. Also of note, the scale of the spending reduction rises rapidly as income quartile increases, particularly when moving from income quartile 3 to 4. This is a function of the increase in spending at quartile 4 (mean spending is almost 80% higher than in quartile 3).

4.4.2 Monetizing changes in health spending risk

To monetize the value of these changes in health spending risk, a stylized utility model is used to calculate the household's change in risk premium after insurance. This approach has been used widely to estimate insurance value in Medicare (Finkelstein & McKnight 2008), Medicare Part D (Engelhardt & Gruber 2010), Japan (Shigeoka, 2014), Thailand (Limwattananon et al., 2015), Ghana (Powell-Jackson et al. 2014), and Mexico (Barofsky 2015). It is assumed that households satisfy a per period budget constraint of $c = y - m$ where y represents income, m household

health spending, c non-health expenditure, and utility is determined under a constant relative risk aversion (CRRA) utility function. The coefficient of relative risk aversion is set to 2.5 and varied from 1 to 4 for sensitivity.

The distribution of health spending m is defined as $P_k(m)$ where k indexes those households with and without insurance [0,1]. The difference between $P_0(m)$ and $P_1(m)$ determines the change in risk exposure from insurance. Household expected utility is calculated as the following:

$$EU[\ y\ ,\ \gamma\ ,\ P_k(m)\ ] = \int_0^{\overline{m}} u(\ max[\ y-m, \gamma y\ ]\ )P_k(m)dm$$

where γ represents an assumed minimum consumption value under which household expenditure does not fall, which is set to 20%. The risk premium represents the quantity of money a risk-averse household would be willing to pay to completely insure against a given risk distribution. The difference in risk premia between those with and without coverage therefore represents the monetary value of the financial risk protection provided by the NHIS.

The risk premium for households with and without insurance is defined as:

$$\pi_k = [\ E_k(y-m) - CE_k\ ] =$$

$$\{\sum_{m=0}^{\overline{m}} max(\ y-m\ ,\ 0.2y\ )P_{t,k}(m)\} - \{u^{-1}[\sum_{m=0}^{\overline{m}} u(\ max(\ y-m\ ,\ 0.2y\ ))P_{t,k}(m)]\}$$

where E_k(y-m) represents the expected value of a household's non-health expenditure and CE_k is the household's certainty equivalent for the same distribution of health spending. The distribution of health spending $P_{t,k}(m)$ is indexed also by t to represent variation the distribution by income group.

Figure 7 summarizes the value of financial risk protection from the NHIS by income quartile and by level of risk aversion. First, observe that the value of financial risk protection increases as risk aversion levels increase. In addition, as indicated by the differences in the scale of health spending by income quartile, the value of risk protection is both an order of magnitude greater for the top income quartile compared to the lower three and also rises faster with increased risk aversion.

5. Implications for Inequality

In this section, the results are compared between the average cost, willingness to pay, and aggregate returns methods and the implications of each approach for

economic inequality are explored. Table 10 compares the mean valuation of inpatient and outpatient care for the average cost and WTP methods and their distribution. Mean values are similar across methods, although average cost has greater variance. For aggregate returns, the mean and distribution of the value for risk protection and the averted mortality are shown. In addition, the average cost subsidy for curative care is also incorporated into the aggregate returns valuation. The table shows that the value of averted mortality is two orders of magnitude greater than the value from risk protection or care subsidies. Their magnitude is based on the underlying malaria mortality risk in Ghana combined with where in the age distribution malaria-related mortality occurs. The largest contributor to mortality averted is from provision of antimalarial medication. Although these medications are not used progressively (see table 6), the higher number of children in low income households combined with the higher value from mortality averted at young ages means the incidence of these gains are progressive. In addition, although the overall magnitude of the reduction in mortality from IRS and ITNs is smaller, access is also distributed progressively. One limitation of the aggregate returns approach is that an assumption about the counterfactual level of each health intervention must be made. The level no coverage is chosen because it is both simple and generally conservative. In general, higher income individuals would have a greater propensity to obtain any health intervention in the absence of public support. Nevertheless, this assumption may minimize additional progressive benefits of certain health interventions.

Table 11 compares measures of overall inequality and headcount poverty by the valuation method used to estimate the in-kind benefit of health spending. For the Gini coefficient, there is a negligible shift in the level of inequality when we switch from average cost to the WTP method. Both imply that the final income Gini coefficient after health spending is valued to be approximately 0.40 and a 90/10 income ratio of about 6. In contrast, because the value of averted mortality is orders of magnitude larger than the value of care subsidies, the aggregate returns method indicates that health-inclusive final income is distributed with a 0.19 Gini coefficient and a 90/10 income percentile ratio of 2.27. Given the monetary magnitude of the gains from averted mortality, full income (inclusive of those monetized mortality gains) implies that headcount poverty is virtually 0 in Ghana, across all three poverty lines measured. Another limitation of the aggregate returns approach is that because more health system interventions are being counted, directly measuring poverty becomes more challenging. One dollar of full income where that dollar is provided either through averted mortality or actual income is not equivalent to one dollar of income since only the latter allows individuals to shift out their budget constraint today. That is, one dollar of monetary income is not the same as one dollar of value from averted mortality because of both when and how it is useful. Adjustment for this difference, although not undertaken here, may be useful in future analyses. Nevertheless, measuring in-kind health spending using the average cost and WTP approaches (although smaller in magnitude) is also subject to the same limitation. Since their magnitude is smaller however, this limitation can be ignored in all except for nations with the highest health spending such as the U.S.

6. Conclusion

This paper compares three methods for estimating the in-kind benefit of health spending and its impact on economic inequality. The first – the average cost approach currently most commonly used in benefit-incidence analysis – is useful because of ease of calculation and clarity in explanation. Most developing nations have sufficiently detailed nationally representative surveys and national health spending accounts data such that the BIA approach is widely feasible and allows comparison across nations. In addition, these methods are accessible to researchers and government officials without extensive training in econometrics or causal inference. However, as discussed above, equating cost to value misses whether care produces health benefits and how our knowledge of health technology can inform valuations and ultimately public resource allocation decisions.

To address this concern, two additional methods for measuring the value of in-kind health spending are also investigated. Given their similarities, the willingness-to-pay methods generates inequality estimates that coincide closely with those found using the average cost approach. It does require more technical skill to apply and additional data (mostly to estimate the opportunity cost of travel time to health care) compared to the average cost method. In contrast, the aggregate returns method implies significantly different estimates of health-inclusive income inequality compared to the average cost and willingness-to-pay. It also requires significantly more technical skill as well as health-specific information across the income distribution compared to the other two methods. Although more onerous, when feasible to implement, aggregate returns provides a comprehensive guide to improving inequality through the health system.

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Tables and Figures

Table 1: Summary statistics data used with multinomial logit model

	(1) Rural	(2) Urban	(3) Overall
Self-care	0.501	0.463	0.487
	(0.006)	(0.008)	(0.005)
Outpatient	0.457	0.490	0.468
	(0.006)	(0.008)	(0.005)
Inpatient	0.043	0.048	0.045
	(0.003)	(0.004)	(0.002)
Opp. Cost Time	7.128	3.096	5.686
	(0.083)	(0.068)	(0.062)
Clinic travel time	60.420	46.805	55.551
	(1.244)	(1.346)	(0.935)
Hospital travel time	146.073	57.728	114.481
	(1.682)	(1.186)	(1.235)
Outpatient Wait time	145.471	164.975	152.747
	(2.649)	(3.103)	(2.029)
Inpatient Wait time	222.898	230.276	225.723
	(17.244)	(27.693)	(15.004)
Outpatient OOP Price	6.171	5.335	5.872
	(0.097)	(0.125)	(0.077)
Inpatient OOP price	0.386	0.333	0.367
	(0.006)	(0.008)	(0.005)
Self-care Net consump.	676.701	988.388	788.161
	(9.250)	(13.405)	(7.778)
Outpatient Net consump.	649.481	974.739	765.794
	(9.249)	(13.317)	(7.770)
Inpatient Net consump.	644.233	979.593	764.158
	(9.266)	(13.317)	(7.788)
Sick days last 2 weeks	5.543	5.728	5.609
	(0.048)	(0.067)	(0.039)
Male (%)	0.462	0.415	0.445
	(0.006)	(0.008)	(0.005)
Age $<$ 18	6.204	6.574	6.328
	(0.091)	(0.134)	(0.076)
Age $\geq$ 18	45.147	41.872	43.919
	(0.312)	(0.367)	(0.239)
N	6503	3620	10123

Sample represents all individuals that report illness or injury in the last two weeks from GLSS 2012-13. Standard deviation in parentheses.

Table 2: Multinomial Logit Model for Care Choices in Ghana

	(1)	(2)	(3)	(4)
	Rural		Urban	
VARIABLES	Outpatient	Inpatient	Outpatient	Inpatient
Male (%)	-0.247***	-0.158	-0.206***	-0.247
	(0.0524)	(0.128)	(0.0728)	(0.170)
# children < 5	0.000420	0.0837	-0.0414	-0.265*
	(0.0377)	(0.0773)	(0.0596)	(0.147)
# adults > 70	-0.00748	0.138	0.0582	0.0961
	(0.0743)	(0.147)	(0.121)	(0.280)
Sick days last 2 weeks	0.0418***	0.111***	0.0562***	0.120***
	(0.00766)	(0.0154)	(0.00971)	(0.0189)
Primary School	-0.276***	0.321	-0.243	-0.478
	(0.103)	(0.283)	(0.158)	(0.325)
Junior High	-0.188	0.0637	-0.153	-0.165
	(0.125)	(0.313)	(0.172)	(0.404)
Senior High	-0.0811	0.0668	-0.193	-0.0995
	(0.131)	(0.355)	(0.174)	(0.407)
> Senior High	0.337	0.0734	0.0902	-0.323
	(0.227)	(0.652)	(0.211)	(0.515)
School Missing	-0.465***	0.156	-0.368	-0.412
	(0.134)	(0.300)	(0.235)	(0.527)
age≤ 2	0.996***	0.802***	0.844***	0.993*
	(0.145)	(0.308)	(0.234)	(0.572)
age 3-5	0.318**	0.401	0.238	0.478
	(0.125)	(0.307)	(0.191)	(0.430)
age 6-18	0.0877	-0.198	0.324***	0.286
	(0.0881)	(0.221)	(0.117)	(0.270)
age 41-60	-0.0980	-0.417*	0.147	-0.189
	(0.0880)	(0.229)	(0.113)	(0.254)
age > 60	-0.0922	-0.408	0.475***	-0.329
	(0.109)	(0.257)	(0.161)	(0.398)
Net consumption	0.301***	0.435**	0.472***	0.313
	(0.0826)	(0.170)	(0.115)	(0.242)
Net consumption^2	-0.0285***	-0.0411**	-0.0772***	-0.0351
	(0.0109)	(0.0201)	(0.0253)	(0.0484)
Constant	-0.288**	-3.615***	-0.516***	-2.900***
	(0.135)	(0.321)	(0.195)	(0.443)
Observations	6,503	6,503	3,620	3,620
ll	-5327	-5327	-3003	-3003
chi2	238.1	238.1	136.9	136.9

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table shows the multinomial logit regression results for urban and rural areas separately in Ghana. Care choices include self-care (reference), outpatient, and inpatient care. Standard errors are clustered by household. Net consumption divided by 1000 for estimation and net consumption^2 by 1,000,000.

Table 3: Estimated Arc Elasticity for inpatient and outpatient care

Panel A: Rural Households

Quartile	Income per capita	Old price	New price	Outpatient Elasticity	Inpatient Elasticity
1	654.2169	0	20	-.0014213	-.002677
2	1302.685	0	20	-.0012668	-.0024516
3	2126.208	0	20	-.0011698	-.0022926
4	4672.005	0	20	-.0009604	-.0019492
1	654.2169	20	40	-.0042944	-.0080763
2	1302.685	20	40	-.0038286	-.0073981
3	2126.208	20	40	-.0035356	-.0069194
4	4672.005	20	40	-.0029046	-.0058854

Panel B: Urban Households

Quartile	Income per capita	Old price	New price	Outpatient Elasticity	Inpatient Elasticity
1	754.2986	0	20	-.0021606	-.0009061
2	1329.35	0	20	-.0018865	-.000797
3	2169.595	0	20	-.0016219	-.0007368
4	5574.956	0	20	-.0010106	-.0006904
1	754.2986	20	40	-.0065559	-.002742
2	1329.35	20	40	-.0057277	-.0024086
3	2169.595	20	40	-.0049277	-.0022221
4	5574.956	20	40	-.0030811	-.0020699

Table 4: Top Causes of Premature Death in Ghana 2016

Cause	Premature Death Rank
Malaria	1
Lower respiratory infection	2
Neonatal sepsis	3
HIV/AIDS	4
Neonatal preterm birth	5
Cerebrovascular disease	6
Congential defects	7
Ischemic Heart Disease	8
Neonatal encephalophathy	9
Protein-energy malnutrition	10

Table 5: Types of health interventions

	Curative	**Preventive**
Personal	Inpatient and outpatient care (Average Cost and WTP)	Malaria Prophylaxis
	Antiretroviral Therapy	Vaccination
		Insecticide-treated net
Public		Indoor Residual Spraying
		Sanitation Infrastructure
		Clean water Infrastructure

Table 6: Malaria Interventions by Wealth Quintile

	IRS[1]	**ITN[2]**	**SP / Fansidar[3]**	**Antimalarials[4]**	**Malaria Prevalence[5]**
Wealth Quintile					
Lowest	29.2	52.2	36.6	41.4	42.1
Second	8.7	53.6	36.1	46.4	39.5
Middle	8.1	43.3	36.1	54.6	24.6
Fourth	4.7	32.9	34.9	51.4	13.9
Highest	5.5	29.5	50.6	52.8	7.5
Total	9.7	43	38.5	48.5	26.7

[1] Percentage of households that received indoor residual spraying in last 12 months
[2] Percentage of children < 5 who slept under an LLITN last night
[3] Percentage of pregnant women 15-49 who received 3+ SP/ Fansidar doses during

last antenatal visit
[4] Percentage who took any antimalarial medication among children under 5 with fever in the last two weeks
[5] Malaria prevalence (microscopy) among children age 6 to 59 months
Source: Ghana DHS 2014

Table 7: HIV Prevalence by Wealth Quintile

	Women	Men	Total
Wealth Quintile	% HIV+	% HIV+	% HIV+
Lowest	1.2	0.5	0.9
Second	3.1	1.8	2.5
Middle	3.2	1.7	2.5
Fourth	4	1	2.5
Highest	2.5	0.8	1.7
Total 15-49	2.8	1.1	2

Source: Ghana DHS 2014

Table 8: Prevalence of Measured Hypertension and Smoking by Wealth Quintile

	Hypertension		Smoking	
	Women	Men	Women	Men
Wealth Quintile				
Lowest	6.7	7.4	1.6	11.2
Second	9.9	7.4	0.3	7.7
Middle	13.1	9.7	0.4	5.9
Fourth	14.3	16.7	0.1	2.4
Highest	17.8	17.9	0.1	1.2
Total 15-49	12.9	12.5	0.4	5.1

Source: Ghana DHS 2014

Table 9: Health Spending and Market Income by Quartile

Health Spending					
	All	Q1	Q2	Q3	Q4
Mean	394	163	265	413	734
SD	2540	682	1238	3289	3578
Median	0	0	0	0	52
75th	208	65	156	260	468
90th	780	364	572	822	1430
95th	1560	780	1170	1560	3016
Mean Spend as % Mean Income	0.046	0.069	0.053	0.051	0.040
Market Income					
	All	Q1	Q2	Q3	Q4
Mean	8473	2366	4957	8093	18478
SD	8329	871	751	1155	11178
Median	6298	2467	4917	7979	14942

Table 10: Value of Health Spending by Method

	Average Cost		**WTP**		**Aggregate Returns**	
	Outpatient	**Inpatient**	**Outpatient**	**Inpatient**	**Risk Protection**	**Mortality Averted**
Mean	300	157	11	106	122	14,426
SD	638	899	3	49	187	6,506
Median	0	0	13	144	34	16,659
25th percentile	0	0	7	43	22	12,030
75th percentile	359	0	13	144	117	18,957

Source: GLSS 2012/13, values in $Ghanaian Cedis.

Table 11: Inequality by Valuation Method

	Average Cost	Willingness to Pay	Aggregate Returns
Gini Coefficients			
Market Income		0.44	
Consumable		0.42	
Final	0.40	0.39	0.19
90/10	6.21	5.98	2.27
Headcount Poverty Index			
$US 1.25 per day	3.00%	6.72%	0.04%
$US 2.50 per day	20.50%	28.82%	0.10%
$US 4.00 per day	45.00%	52.10%	0.40%

Figure 1: Outpatient Utilization by decile

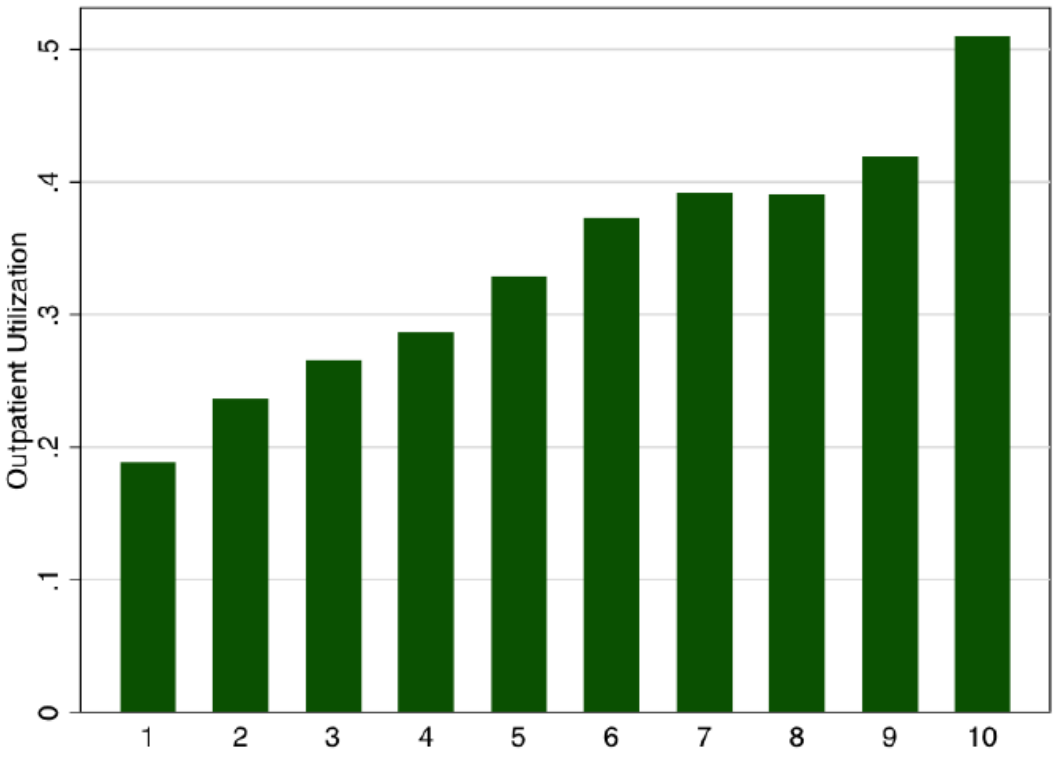

Figure 2: Inpatient utilization by decile

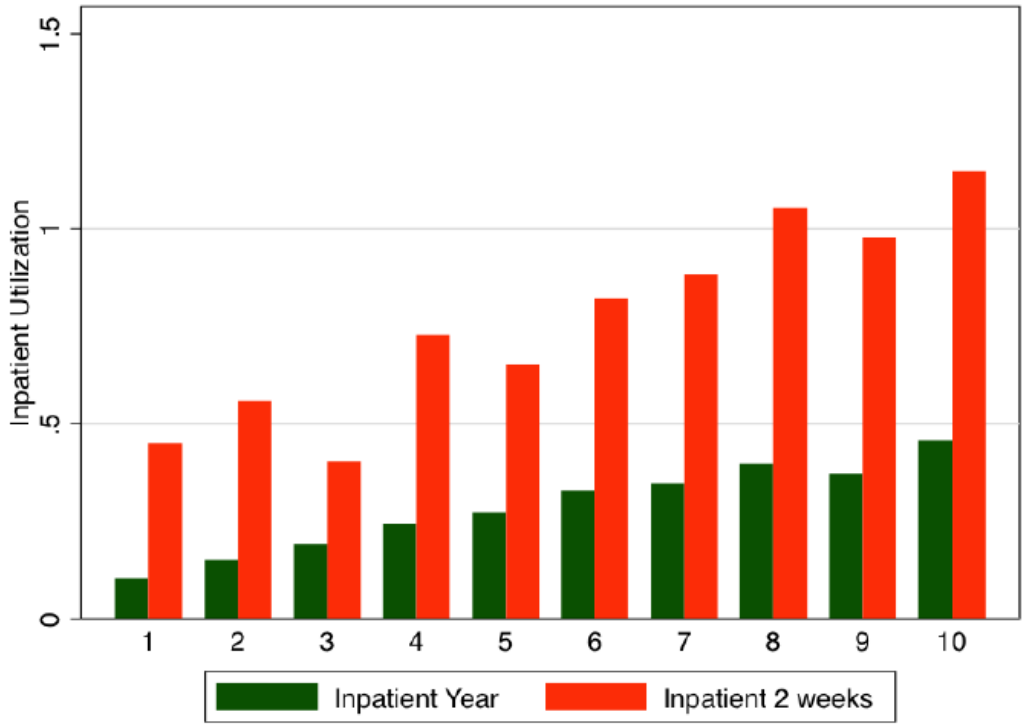

Figure 3: Value of Averted Mortality from Health Interventions

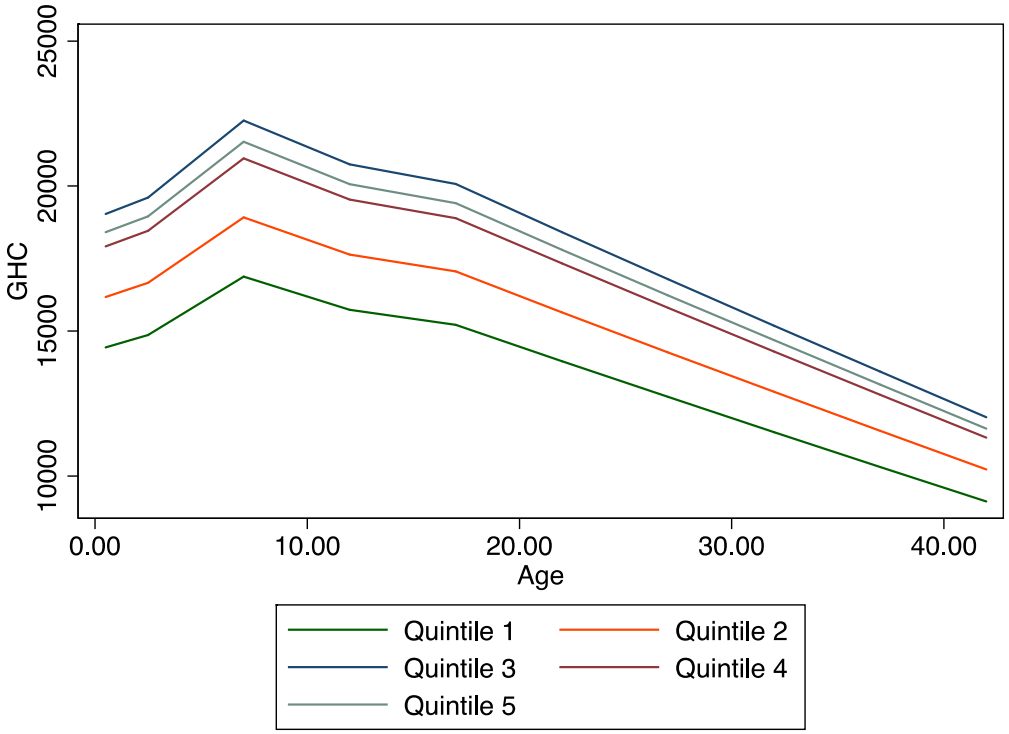

Figure 4: Effect of NHIS insurance on medical expenditure, quartile 1

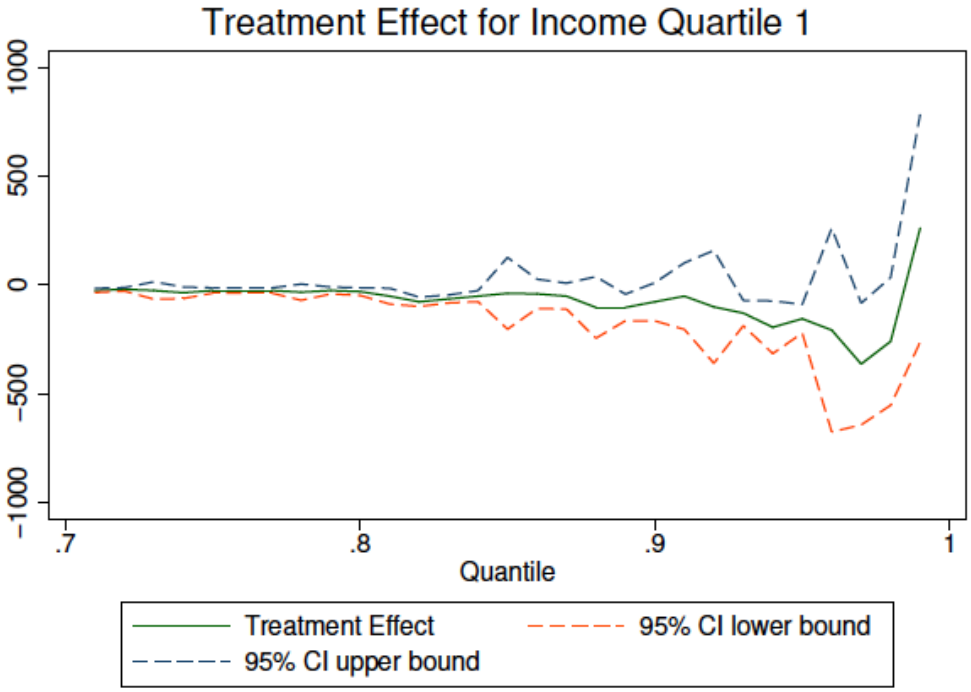

Figure 4 shows the treatment effect ($GHC) of NHIS insurance by medical expenditure centile among households with income in the lowest market income quartile. Standard errors are clustered at the survey level.

Figure 5: Effect of NHIS insurance on medical expenditure, quartile 2

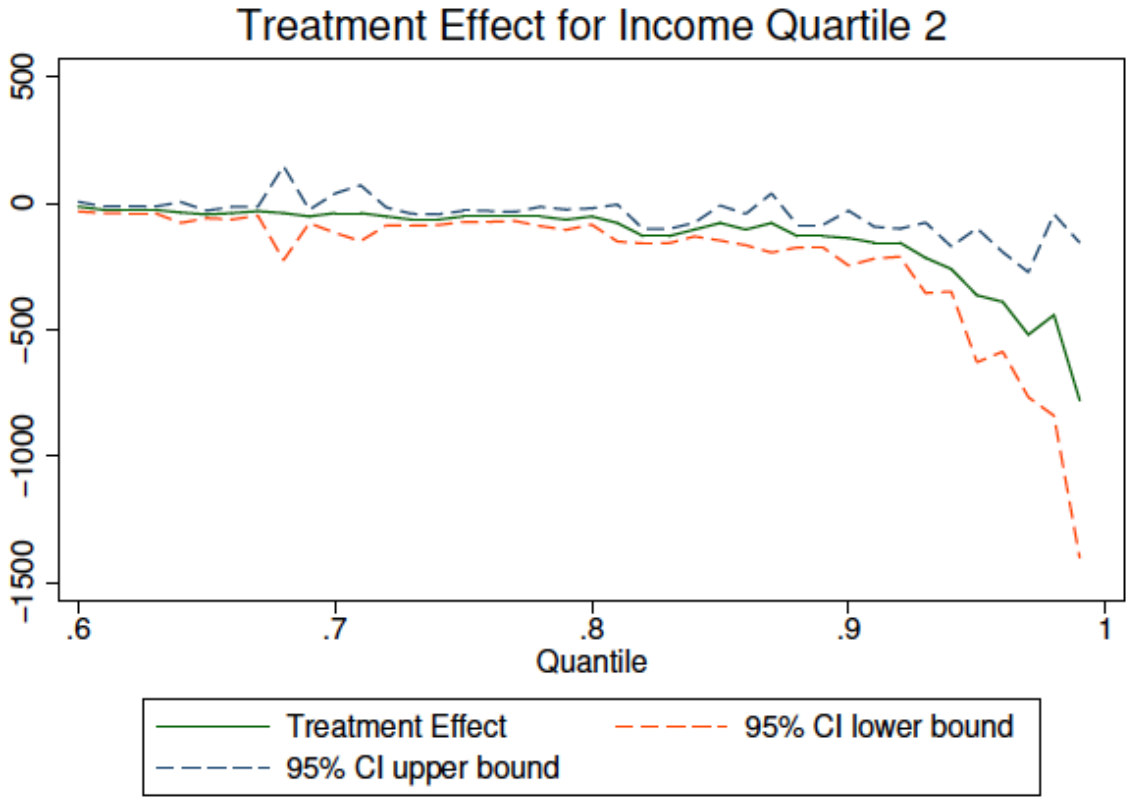

Figure 5 shows the treatment effect ($GHC) of NHIS insurance by medical expenditure centile among households with income in the second market income quartile. Standard errors are clustered at the survey level.

Figure 6: Effect of NHIS insurance on medical expenditure, quartile 3

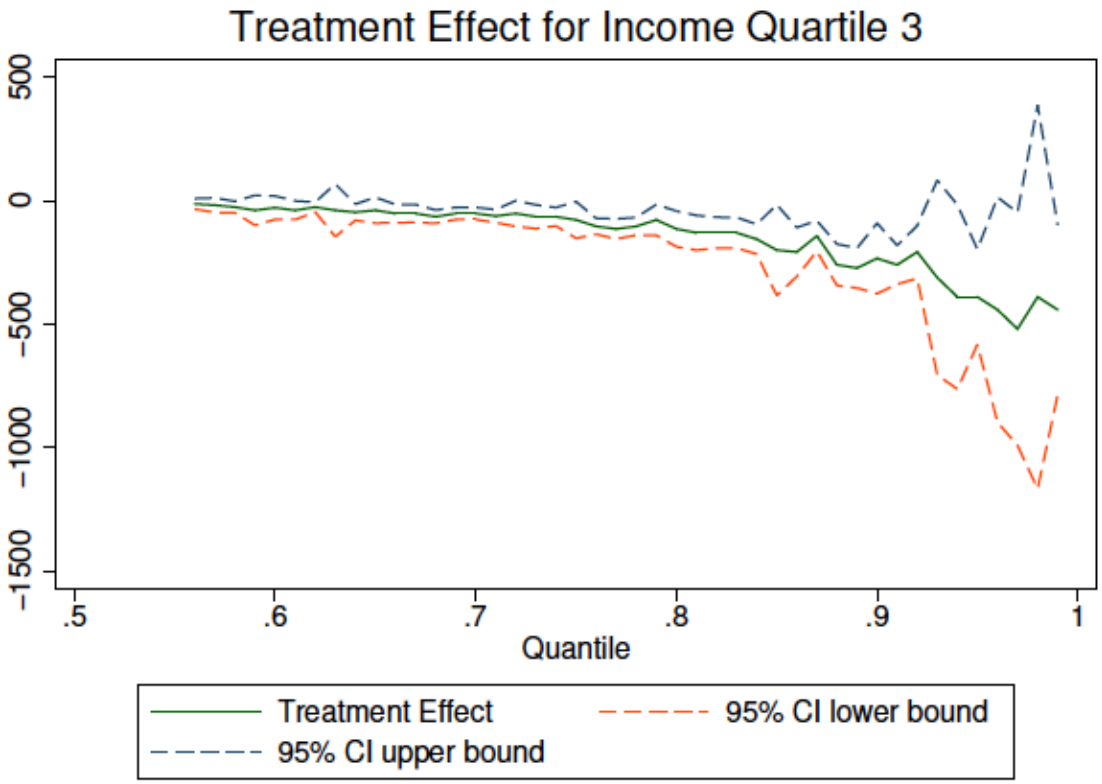

Figure 6 shows the treatment effect ($GHC) of NHIS insurance by medical expenditure centile among households with income in the third market income quartile. Standard errors are clustered at the survey level.

Figure 7: Effect of NHIS insurance on medical expenditure, quartile 4

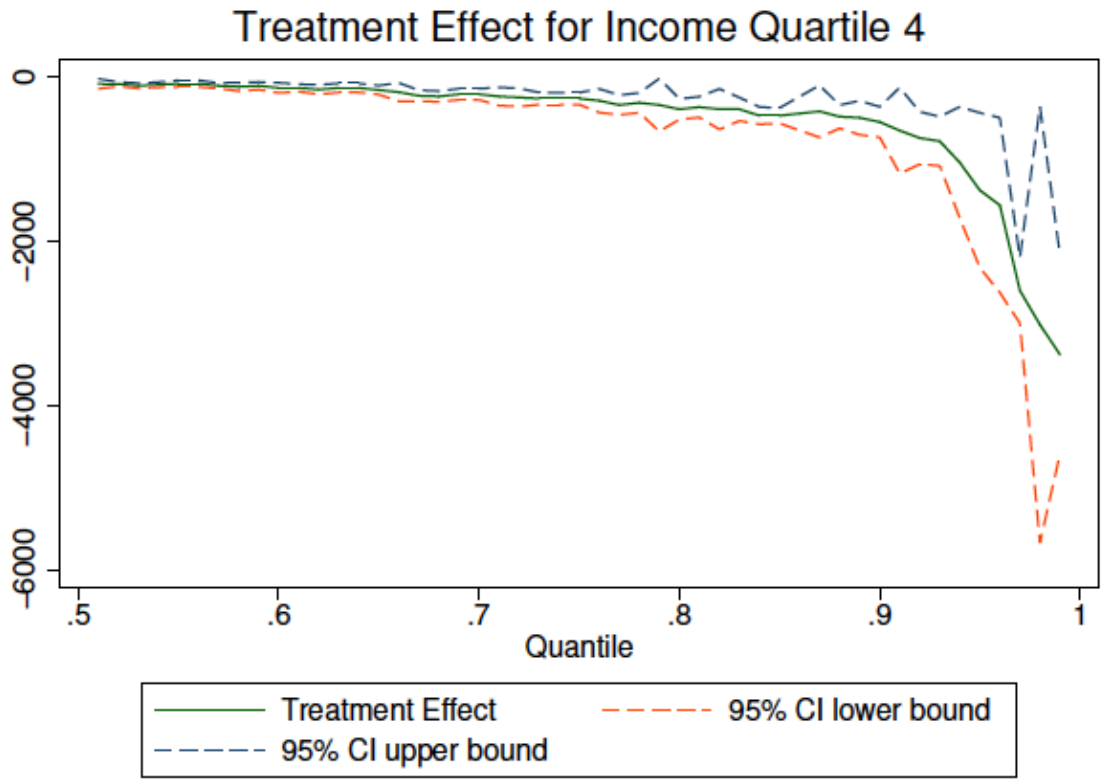

Figure 7 shows the treatment effect ($GHC) of NHIS insurance by medical expenditure centile among households with income in the highest market income quartile. Standard errors are clustered at the survey level.

Figure 8: Change in Risk Premium from NHIS by Income Quartile and Level of Risk Aversion

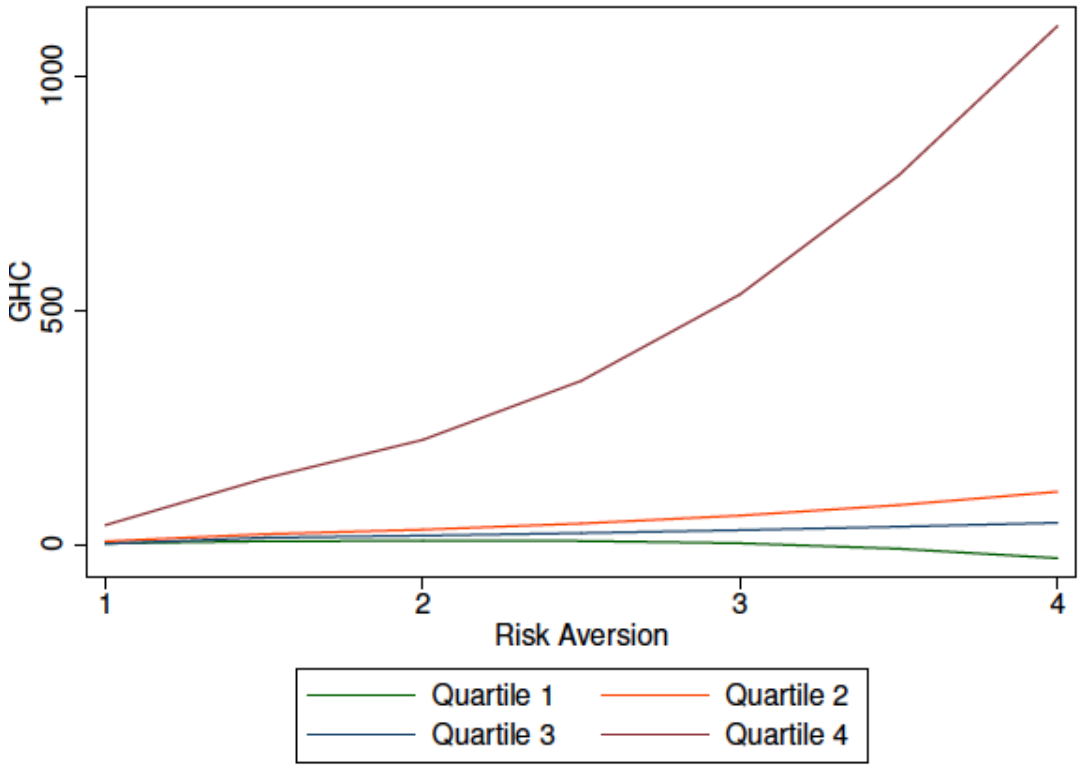

Figure 8 shows the change in risk premium ($GHC) from NHIS insurance by levels of risk aversion (coefficient of relative risk aversion varying from 1 to 4) and by income quartile.

Appendix:

Figure A.1: Insurance Coverage by Decile (Ghana) GLSS 2004/05 and 2012/13